RECONSTRUCTION OF HIGH QUALITY HOLOGRAPHIC IMAGE USING DOUBLE-SAMPLING FRESNEL DIFFRACTION METHOD

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Abstract- During the past several years dynamic holographic projection has been used for its high diffraction efficiency, low power consumption, high-contrast. With the explosive developments of deep learning and computer generating hologram has become an effective way to achieve real–time and high–quality holographic images. In this paper, we focus on the rapid progress of machine learning–based holographic images. The generation principles and algorithms of stochastic gradient descent (SGD), and double-sampling Fresnel diffraction (DSFD) with neural networks are used. This method will achieve better reconstruction quality.

I. INTRODUCTION

With the development of the many techniques of the spatial light modulator (SLM), dynamic holographic projection with an SLM has been researched deeply [1,2]. Dynamic holographic projection has attracted with its high diffraction efficiency, low power consumption and high-contrast [3–6]. In SLM technique pixel size is large, the diffraction angle is limited. Hence the lensless holographic projection of optical image is much smaller than that of the conventional projector when the projection distances are the same. So the fast Fourier transform (FFT) with single-FFT is the common algorithm to compute the Fresnel diffraction field [7]. Since the diffraction angle is limited by the spatial resolution of the spatial light modulator (SLM), using a divergent spherical beam to illuminate a SLM is an effective method to increase the projection angle. In this paper, we focus on a double-sampling Fresnel diffraction algorithm to enlarge the sampling range is proposed in holographic projection. In this paper, a double-sampling (DS) Fresnel diffraction algorithm with FFT, which eliminate the traditional restriction of the sampling range. In the DS Fresnel diffraction algorithm, the Fourier plane is employed as an intermediate plane, and the sampling interval is demagnified with small radius of the spherical beam then the sampling range on screen is enlarged accordingly, the enlarged spatial frequency range of the spherical illumination is fully utilized, which breaks the limitation of the sampling range induced by the existing Fresnel diffraction algorithms. The hologram can be easily optimized by the iterative algorithm [7] to provide a quality holographic image.

II.LITERATURE REVIEW

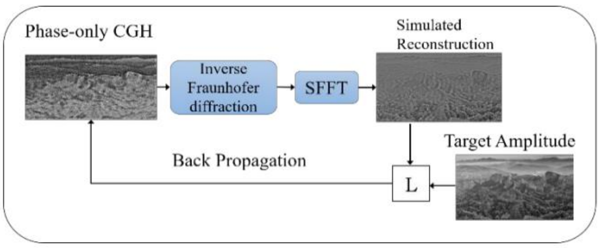
Peng [9] and Wu [10] proposed to compute the Computer Generated Hologram by machine learning methods. In this method the time for calculating the CGH is reduced to less than 0.2 seconds with single-fast Fourier transform and the angular spectrum diffraction algorithms. This method cannot obtain large field of view (FOV) angles, so it is not large enough for binocular observation for near-eye display.

Chang [11] and Qu [12] suggested an image amplified lensless holographic projection.

However, the evaluation of their computergenerated hologram (CGH) requires a sophisticated iterative algorithm that is unfortunately time-consuming. In each iteration of the calculation, several Fourier transforms and inverse Fourier transforms have to be implemented

III.PROPOSED METHOD

In order to further improve the image quality and reduce the calculating time of the CGH, the method based on the combination of the DSFD algorithm and machine learning is proposed. Gradient descent is a way to minimize an objective function parameterized by a model's parameters by updating the parameters in the opposite direction of the gradient of the objective function to the parameters. We first implement stochastic gradient descent (SGD) to optimize the loss function in Equation 1, see Fig. 4. We give an initial random phase on the SLM plane and calculate the complex field on the image plane with the DSFD algorithm. Then we calculate the loss between the target image and the simulated projection image. Finally, we backpropagate the error between target image and simulate reconstruction with a stochastic descent optimization algorithm to update the phase-only holograms. Since the iterative procedure of the SGD does not perform the inverse calculation of the light propagation and only needs to calculate the diffraction once, time consumed is only half of the traditional GS method for each epoch. In addition, by adjusting the learning rate, the SGD algorithm converges much faster than the traditional GS method.



DOUBLE-SAMPLING FRESNEL DIFFRACTION ALGORITHM AND THEORETICAL FORMULA

When a divergent spherical beam illuminates a SLM (here we assume the SLM is transmissive to simplify the analysis), the propagation from the SLM to the screen is shown in Fig. 1. The plane of the illumination point source (Fourier plane) is taken as a intermediate plane, and the calculation of the diffraction pattern on the screen is divided in two steps. The first step is the backward propagation from the SLM to the intermediate plane (the plane of the illumination point source). Fraunhofer diffraction can be used in this simulation since the divergent illumination is implemented [19],

$$U_1(x_1) = \exp\left(\frac{\mathrm{i}kx_1^2}{-2r}\right)\mathcal{F}^{-1}[U_0(x_0)]$$

where U0(x0) and U1(x1) are the complex amplitude distribution on the input and intermediate planes, respectively, r2
is the radius of the divergent spherical illuminated beam. When FFT is used here, the size of the diffraction pattern on the intermediate plane Lr is determined by [7] L0Lr = rλN or Δx0Δx1 = rλN ;
where Δx1 is the sampling interval on the intermediate plane. Since it is a Fraunhofer diffraction, the calculation of the complex amplitude distribution on the intermediate plane can meet the sampling theorem easily only if the sampling of U0(x0) could meet the sampling theorem. The second step is the Fresnel diffraction from the intermediate plane to the screen [20],2

$$U(x) = \exp\left[\frac{\mathrm{i}kx^2}{2(z+r)}\right]\mathcal{F}\left\{U_1(x_1)\exp\left[\frac{\mathrm{i}kx_1^2}{2(z+r)}\right]\right\}$$

where U(x)is the complex amplitude distribution on the screen2

When S-FFT is used here, the size of the optical image on the screen Lz is determined by [7] $LrLz = \lambda(z + r/N)$ or $\Delta x1\Delta x = (\lambda z + r)/N3$

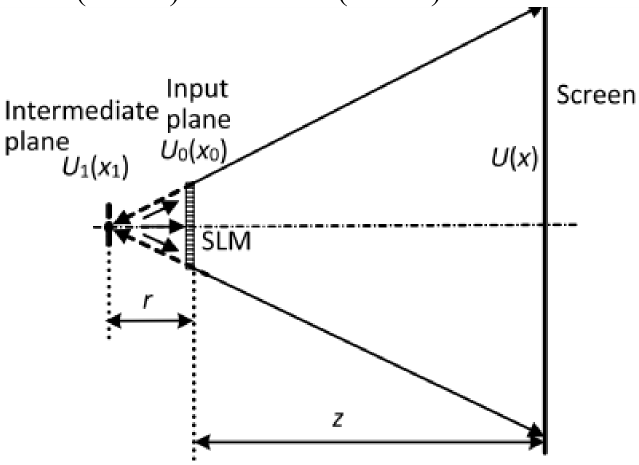
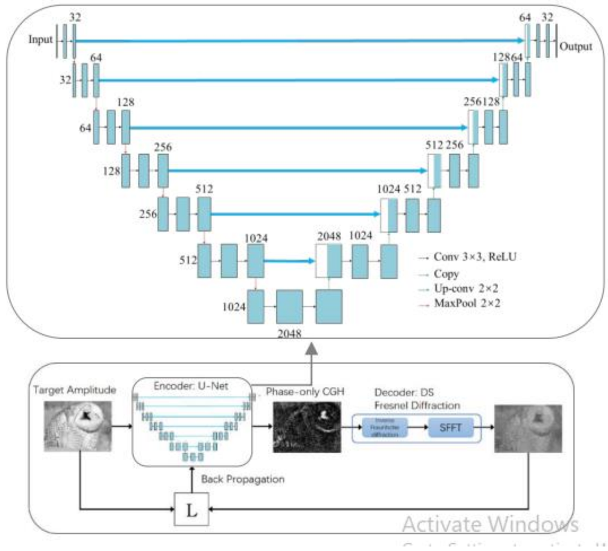


Fig. 1. Propagation from the SLM to the screen when the incident beam is a divergent spherical one.

Despite the fact that the SGD algorithm can reduce the computation time of holograms by more than half, we still need a fast way to obtain the phase-only hologram. We then combine the above DSFD algorithm with a neural network to form our DSFD-Net model. The DSFD-Net model can be trained in an unsupervised learning method of the mapping from the target image to the hologram without labels. The generation and reconstruction of phase-only CGH can be depicted as the encoding and decoding process of target images. Our neural network works as the encoder part in the system and translates the target image to the corresponding phase-only CGH. The output of the network is the input of our decoder. The decoding part is the fixed DSFD model which has been described above. The architecture of our training procedure and the U-Net is shown in Fig. 5. As an unsupervised learning model, the data sets and validation sets need not be labeled



The U-Net model uses a down-sampling and then upsampling structure. The use of a skip connection at the same stage ensures that the final CGH output incorporates more low-level features and retains all the information in the image. This advantage is very suitable for CGH computation. The length and width of the image tensor are reduced by half after each down-sampling in our U-Net, and the geometric feature extraction of the input image is realized after down-sampling repeats 6 times. When the next 6 times of up-sampling is implemented, the reconstructed original size image tensor is obtained. In order to avoid the disappearance of the gradient during the network training, the residual connection is employed to realize the cross-layer transfer of the gradient. After each convolution, the batch normalization is performed to avoid overfitting. In the U-Net training procedure, we use the amplitude of 1920×1080 image as the training input. The U-Net outputs the corresponding CGH. We simulate the physical diffraction processing with the CGH generated by our U-Net

IV.RESULT AND DISCUSSION

Flective SLMs is smaller and the diffraction angle is larger; hence, it is often used in holographic projection. While it makes the optical system more complex. Fortunately, the

DS Fresnel diffraction algorithm has an important feature: the size of the holographic image is limited by the active area but not by the pixel size of the SLM. Therefore, the existing SLM products, whether reflective or transmissive, whether the resolution is high or low, all could be used in the system only if the size of the active area is large. Of course, pixel number should be as many as possible to improve the resolution of the optical image.

We simulate the light propagation on Google Colab with PyTorch, which is essentially based on python and CUDA, to demonstrate the performance of different algorithms with GPUs. The GPU is NVIDIA Tesla P100 with 16GB memory. To keep consistent with the experimental situation, the pixel pitch of the CGH is set as and the resolution is dLSLM = 8μm 1920×1080. The wavelength of laser is 532nm. The distance between the diverging point light source and the hologram is 2.6 cm and the propagation distance is 26 cm. Fig. 6 shows the simulated results of the SGD method and GS method. We use the mean square error (MSE) and peak signal-to-noise ratio (PSNR) to quantify the quality of the reconstructed images.

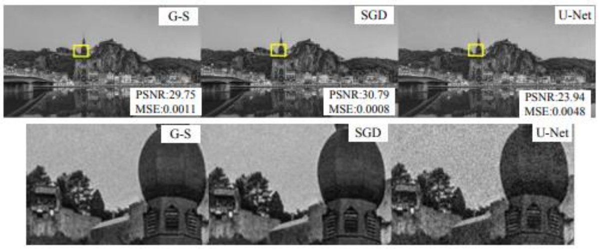


Fig. 7. Performance evaluation of our U-Net and the iterative methods. The PSNR and MSE value indicate the reconstruction image quality of the algorithm.

V.CONCLUSION

This paper, the machine-learning techniques are introduced to generate the hologram used in an image magnified lensless holographic projection system. Compared to the iterative method, neural network can compress computation time to several milliseconds level. Meanwhile, the neural network can match various projection systems to meet the corresponding requirement of the near-eye display devices. The proposed method is applicable to augmented reality displays, virtual reality displays and hopefully other real-time 3D display systems in future.

When a divergent spherical beam illuminates a SLM, the projection angle of the SLM in the holographic projection will be increased physically. With the DS Fresnel diffraction algorithm, the traditional restriction of the sampling range is broken, and magnification of the optical image in lensless holographic projection is obtained when r is a small value. Furthermore, the zero-order background noise of the SLM is weakened obviously. As our next work, we plan to develop.

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